

Essays on Return and Volatility on World Stock Markets

By

Jia Liu

Submitted to the graduate degree program in Economics and the Graduate Faculty of the University of Kansas in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

---

Chairperson Shigeru Iwata

---

Shu Wu

---

Ted Juhl

---

Jianbo Zhang

---

Yaozhong Hu

Date Defended: May 15, 2013

The Dissertation Committee for Jia Liu  
certifies that this is the approved version of the following dissertation:

Essays on Return and Volatility on World Stock Markets

---

Chairperson Shigeru Iwata

Date approved: May 15, 2013

# **Abstract**

This research is mainly focused on investigating volatility dynamics of world stock returns. More specifically, the main goal is to capture co-movements and analyze dynamic transmission mechanisms of volatility of stock returns across the world. Understanding the mechanisms linking international equity markets is important for not only policymakers but also fund managers who make investment decisions based on the international risk diversification. But existence of co-movements in world stock markets is lack of evidence in the existing literature.

Chapter 1 gives a detailed literature review and clarifies the marginal contribution of this research. The chapter begins with introducing the importance of related research on this topic. Secondly, a number of influential literatures on the related field are reviewed. It shows that the existing literature is not able to capture a clear trend of co-movement across world stock markets. The problem could be resulted from model selections, data construction, and sample sizes and etc. Those questions are addressed in this dissertation research.

In Chapter 2, co-movements across worldwide stock markets are investigated. A dynamic factor model is designed to decompose stock return volatility into three orthogonal factors: the world factor, the regional factor and the local factor. The three factors are assumed to be well suited for explaining all the variation of volatility. Fourteen countries are included in the empirical study in order to cover both developed and emerging stock markets. The historical volatility growth decomposition is conducted to analyze contributions made by different factors to the volatility growth for each market. The results show that there exist co-movements which are able to account for more than 50% of variation of volatility for most of countries. The world factor turns

out to be significant for North American and Latin American markets; nevertheless the regional factor is important for Europe and Asia.

In Chapter 3, a modified dynamic factor model is conducted to investigate spill-over effects between different stock markets or regions. It begins with examining the dominant position of the U.S. in world stock markets, followed by analysis on the effect of U.S. stock market on Asian markets. Linkage between Asian stock markets and Latin American markets are also investigated. Moreover, the author extended the time horizon and adjusted the sample of countries in order to examine effects of financial integration on world stock markets. The results show that the dominance of the U.S. stock market in world stock markets has been getting weaker since international financial markets became more integrated. Emerging stock markets have become more independent of developed markets after financial globalization.

# Acknowledgement

First and foremost, I would like to express my sincere gratitude to my adviser, Professor Shigeru Iwata. I took all econometrics classes and international finance classes from Professor Iwata for five semesters. His classes were challenging, but extremely helpful, and more importantly, inspiring. In his classes, I not only learned econometric methodologies, but also got inspired by his dedication to economic research. I soon became highly interested in financial econometrics and decided to work on this area for my dissertation. Professor Iwata kindly agreed to work with me as my dissertation adviser and provided remarkable suggestions and advises on my work all the time. During years of working with Professor Iwata, we met at least once a week and he was always available, supportive, and helpful. Without Professor Iwata's supervision, all of this dissertation work would be impossible.

My gratitude is extended to the faculty of my dissertation committee: Professor Shu Wu, Professor Ted Juhl, Professor Jianbo Zhang, and Professor Yaozhong Hu from the Department of Mathematics. I would like to thank them for being supportive and giving valuable suggestions throughout my dissertation research process. I would especially thank Professor Zhang for agreeing to join the committee to replace one of the members due to an emergency.

I also would like to thank all my classmates from the Macroeconomics workshop. During two years of attending the workshop together every Thursday, we shared research experience and learned from each other. I appreciate all inputs they have provided to me when I was presenting my work at the meetings.

Last but not least, I need to thank my family for standing by me under any circumstances. When I decided to quit my job and came to the U.S. to pursue a Ph.D., my parents gave me enormous support, morally and financially. Their faith in me has been always encouraging and made me more confidence to pursue my dreams. Without their unconditional love and support, I wouldn't have been able to make this journal possible.

# Contents

Contents .....	vii
List of Tables .....	ix
List of Figures .....	x
1. Literature Reviews .....	1
1.1 International Transmissions of Stock Returns and Volatilities .....	1
1.2 Leverage Effects and Volatility Feedback Effects .....	6
2. Volatility Dynamics of World Stock Returns .....	10
2.1 Introduction .....	10
2.2 Empirical Framework .....	13
2.2.1 Data .....	13
2.2.2 Model Setup .....	14
2.2.3 Computational Procedure .....	17
2.3 Empirical Results .....	18
2.3.1 Model Estimation .....	18
2.3.2 Historical Volatility Growth Decomposition .....	20
2.4 Conclusions .....	33
3. Spill-over effects among world stock markets .....	35
3.1 Introduction .....	35

3.2	Spill-over Effects Analysis.....	36
3.2.1	Spillovers from the U.S. to the rest of the world .....	36
3.2.2	Spillovers from the U.S. to Asian stock markets .....	38
3.2.3	Spillovers between Asian and Latin American stock markets.....	40
3.3	Financial globalization effects on world stock markets .....	41
3.4	Conclusions .....	43
Appendix:.....		45
References .....		48



## List of Tables

Table 1: Classification of 14 countries .....	14
Table 2: Classification of 9 countries .....	41
Table 3: Variance decomposition for 9 countries .....	41

## List of Figures

Figure 1: VIX over time during 1993 to 2009 .....	12
Figure 2: Historical stock return volatility in the U.S.....	12
Figure 3: The world factor for stock indices returns.....	18
Figure 4: The world factor for stock indices return volatility.....	20
Figure 5: Historical volatility growth decomposition in North America.....	22
Figure 6: Historical volatility growth decomposition for Europe.....	23
Figure 7: Historical volatility growth decomposition for Asia .....	25
Figure 8: Historical volatility growth decomposition for Latin America. ....	26
Figure 9: Growth of volatility and factors for all regions .....	27
Figure 10: Average growth of volatility and factors in North America .....	29
Figure 11: Average growth of volatility and factors in Europe .....	30
Figure 12: Average growth of volatility and factors in Asia .....	31
Figure 13: Average growth of volatility and factors in Latin America .....	32

# **1. Literature Reviews**

## **1.1 International Transmissions of Stock Returns and Volatilities**

Understanding the transmission mechanisms linking international equity markets is important for not only policymakers but also fund managers who make investment decisions based on the international risk diversification. According to the finance theories, it is believed that there are potential gains on international diversified portfolios by investing in different national stock markets which are not perfectly correlated and correlation structures among those markets are stable. This has led economists and finance specialists to investigate the contagion and interdependencies among international equity markets.

Change in the volatility of stock markets can have important effects on capital investments, consumptions, and other business cycle variables. Some papers have related the stock market volatility to the time-varying volatilities of a variety of economic variables. The stock volatility reflects uncertainty about the future course of the economy, which shows up later in the realized growth rates of nonfinancial macroeconomic variables such as the money supply, consumption, and investment. In reverse, the expectation of future macroeconomic behaviors also contributes into changes in the stock volatility. Due to closer economic connections among countries all over the world, international stock markets appear to be more contagious and interdependent.

Besides the economic connections, some linkage channels are thought to arise from information shocks which result in interdependent equity markets moving in harmony with each other. The remarkable technological advances in the computer and communication industries have made it much easier for a large number of people to learn about and react to information

very quickly. They have also made it possible for financial markets to provide liquidity for investors around the world. As a consequence, there are large incentives for investors to get and act on the new information. Because the new information spreads more quickly, the rate at which prices change in response to the information has also accelerated. More recently, the linkage originating from unanticipated shocks in a particular country or a group of countries, which spreads to international equity markets, has a large impact on international markets even where there are no strong economic linkages connecting the economies.

There has been a large amount of literature on the international transmission of stock returns and volatilities. On the study of return and volatility spillover effects across international equity markets, most of the existing literature focuses on using GARCH and SV models to capture features of stock returns and volatilities.

One of the most important contributions toward a better understanding of international stock returns co-movements is King, Sentana and Wadhwani (1994), published in *Econometrica*. The paper investigates the time-variation in the co-variances between stock markets and assesses the extent of capital market integration. They use data on sixteen national stock markets over the period 1970-1988 to estimate a multivariate factor model in which the time-varying volatility of returns is induced by changing the volatility in the underlying factors. They assume that excess returns depend both on innovations in observable economic variables and on unobservable factors. They allow the conditional variances of the underlying factors to vary over time and parameterize this in terms of GARCH processes. Their theoretical model can be understood as a dynamic version of the Arbitrage Pricing Theory. They reach the conclusion that the global stock markets are not integrated. They are able to reject the null hypotheses that the idiosyncratic

risk is not priced, and that the “price of risk” associated with the relevant factors is the same across countries. In addition, “unobservable” factors have historically been more important in explaining stock returns than the “observable” factors.

Another interesting paper “Emerging equity market volatility”, written by Bekaert and Harvey (1997), provides an approach that allows the relative importance of the world and local information to change through time in both the expected returns and conditional variance processes. They apply a GARCH model with the world factor to 20 emerging markets over the period 1976-92. They conclude that the decomposition of the variation sources in volatility sheds light on how each market is affected by world capital markets and on how this impact varies over time. The evidence in this paper suggests that volatilities decrease in most of countries that experience the liberalization. There is a sharp drop in the volatility in five countries in their 20 emerging markets sample. Even after controlling for all of the potential influences on the time-series and cross-section of the volatility, they find that capital market liberalizations significantly decrease the volatility in emerging markets.

Angela Ng (2000) wrote a paper on volatility spillover effects from Japan and the U.S. to the Pacific-Basin. The author constructs a volatility spillover model which allows the unexpected return of any particular Pacific-Basin market to be driven by a local idiosyncratic shock, a regional shock from Japan and a global shock from the U.S. The particular interest of this paper is the impact of capital market liberalizations on volatility spillovers. The tests in this study are based on the ARCH family of models. The major findings are threefold. First, the regional factor and the world factor are both important for the market volatility in the Pacific-Basin region, although the worldwide influence explained by the world factor tends to be greater. Secondly,

the relative importance of the regional factor and the world factor is influenced by the important liberalization events. Third, the proportions of the Pacific-Basin market volatility captured by the regional and world factors are generally small.

Francis X. Diebold and Kamil Yilmaz (2009) investigate the equity market spillovers in the Americas. Five equity markets in the Americas are chosen: Argentina, Brazil, Chile, Mexico and the U.S. They explore study in both of non-crisis and crisis episodes, 1992-2008, including spillover cycles and bursts. They claim that they find some striking evidence of divergent behaviors in the dynamics of return spillovers and volatility spillovers: return spillover effects display gradually evolving cycles but no burst, whereas volatility spillovers display clear bursts that correspond closely to economic events.

Most of the literature discussed above is only focused on volatility dynamics and transmissions in one region. A more recent paper published in The Journal of Finance was titled “International Stock Return Co-movements”, written by Bekaert, Hodrick and Zhang. They study the co-movements between the returns on country-industry portfolios and country-style portfolios for 23 countries, 26 industries, and 9 styles during 1980-2005. A simple linear factor model is used in this paper to capture co-movements of international asset returns. The factor structure and the risk loadings on the factors are allowed to change every half year, so the model is claimed to be general enough to capture time-varying market integrations and to allow for risk sources other than the market. Little evidence of a trend in correlations of country returns is found, except within Europe. Second, the globalization process has not yet led to large and permanent changes in the correlation structure across international stocks.

Corradi, Distaso and Fernandes (2009) propose a framework to gauge the degree of volatility transmissions among international stock markets by deriving tests for conditional independence among daily volatility measures. They investigate volatility spillovers among the stock markets in China, Japan, and the U.S. from 2000 to 2005. The testing procedure involves two steps. In the first stage, they estimate the integrated variance using the return data by means of realized measures in order to avoid misspecification risks. In the second step, they then test for the conditional independence between the resulting realized measures. The empirical study evinces that volatility transmissions between Japan and the U.S. runs in both directions, whereas they find stronger evidence of spillovers running from China to either Japan or the U.S. than vice-versa.

Other than the ARCH family of models and SV models, a dynamic factor model is used in this study to investigate whether or not it's a good fit for the decomposition of volatilities in the international stock markets. The dynamic factor model can cope with many variables without running into scarce degrees of freedom problems. In addition, idiosyncratic movements which possibly include measurement errors and local shocks can be eliminated. The dynamic factor model has been successfully used in the research on international business cycle with large dataset.

One of the most important contributions into the study on international business cycle by using the dynamic factor model is Christopher Otrok and Charles H. Whiteman (1993). The paper designs and implements a Bayesian dynamic latent factor model for a vector of data describing the economy. Posterior distributions of parameters and the latent factors are analyzed by the Markov Chain Monte Carlo methods, and coincident and leading indicators are computed

by using posterior mean values of the current and predictive distributions for the latent factors. They provide feasible computation techniques for our empirical study to handle large time series dataset in the application of a dynamic factor model.

In 2008, Marco Del Negro and Christopher Otrok develop a dynamic factor model to measure changes in international business cycle by making parameters time-varying. This paper develops and estimates the model with time-varying factor loadings and the stochastic volatility in the innovations for both common factors and idiosyncratic components. This model is used as a measurement tool to characterize the evolution of international business cycle since 1970. The model, which explicitly allows for changes in factor loadings, is a natural framework to analyze recent policy debates on the supposed decoupling of emerging markets economies. They also claim that the model can be applied to the forecasting literature and the literature for pricing assets and portfolio allocations.

## **1.2 Leverage Effects and Volatility Feedback Effects**

Some econometrics models have been successfully developed to explain relationships between stock returns and volatilities. The Black-Scholes model, first introduced by Fischer Black and Myron Scholes (1973), has been widely used as an equity pricing model by depending stock returns on volatilities. However, there is a big shortcoming in this model about the assumption that the underlying volatility is constant over the life of the derivative, and unaffected by the changes in the price level of the underlying security. One striking characteristic of the stock market is that the volatility of returns can be very different at different times. Long-observed features of the implied volatility surface such as volatility smile and skew indicate that the implied volatility does tend to vary over time. To solve this problem, two ways of modeling



this feature have been developed. One way is to let the conditional variance be a function of the squares of previous observations and past variances. This leads to the autoregressive conditional heteroskedasticity (ARCH) based model which was developed by Engle (1982) and surveyed in Bollerslev, Engle and Nelson (1994). The other way is to specify the variance to follow some latent stochastic process. Such models, referred to as stochastic volatility (SV) models, appear in the theoretical finance literature on pricing options.

There has been a large amount of literatures on relationships between stock volatilities and returns. The fundamental paper on this subject was written by John Y. Campbell and Ludger Hentschel, “No news is good news: An asymmetric model of changing volatility in stock returns”, published in the Journal of financial Economics in 1992. The authors develop a model (quadratic generalized autoregressive conditionally heteroskedastic, or QGARCH) with changing variances to capture the volatility feedback effect. Such asymmetric model is claimed to help explain the negative skewness and excess kurtosis of U.S. monthly and daily stock returns over the period 1926-88. They conclude that the volatility feedback effect can be important in explaining excess returns during periods of high returns, but little evidence is found in this paper that the volatility feedback effect has a big effect on returns at normal times.

Guojun Wu (2001) published a paper in The Review of Financial Studies, named “Determinants of Asymmetric Volatility”, to examine if the leverage effect is an important determinant of the asymmetric volatility along with the volatility feedback effect. The model he uses in the paper specifies a stochastic volatility dividend process. There are two state variables in the model, which extend the classical Campbell and Hentschel (1992) one-factor volatility feedback framework. He finds out that the leverage effect and the volatility feedback effect both

play very important roles in generating the asymmetric volatility. For the monthly and weekly CRSP value-weighted index, the leverage effect contributes more to the negative correlation between returns and return volatilities.

Both papers described above used the GARCH model to investigate the asymmetric volatility. Some authors argue that stochastic volatility (SV) models are able to provide a faster and more efficient procedure by exploiting the Markov Chain Monte Carlo (MCMC). Kim, Shephard and Chib (1998) published a paper in the *Review of Economic Studies*, named “Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models”, in which the issue of model choice using non-nested likelihood ratios and Bayes factors is investigated. They develop a highly effective method that samples all the unobserved volatility at once using an approximating offset mixture model. These models are used to compare the fit of the stochastic volatility and GARCH models. The authors argue that a formal comparison of the SV model in relation to the popular heavy tailed version of GARCH models is also provided for the first time. The results in this paper provide a unified set of tools for a complete analysis of SV models that includes estimation, likelihood evaluation, filtering, diagnostics for model failures, and computation of statistics for comparing non-nested models.

In 2006, a paper extended Kim et al.’s work to model with the leverage effect. It was written by Omori, Chib, Shephard and Nakajima, published in *Journal of Econometrics*. The approach implemented in this paper relies on the novel idea of approximating the joint distribution of the outcome and volatility innovations by a suitably constructed ten-component mixture of bivariate normal distributions. They illustrate the ideas on daily returns of the Tokyo

Stock Price Index from 1998 through 2002. The conclusion is reached that the SV model with the leverage effect is preferred over the competing models in terms of efficiency.

## **2. Volatility Dynamics of World Stock Returns**

### **2.1 Introduction**

The previous empirical studies on interrelationships of the major world stock indexes have not provided consistent results. King, Sentana and Wadhwani (1994) investigate the time-variation in the co-variances between stock markets and assess the extent of capital market integrations. They conclude that the global stock markets are not integrated and “unobservable” factors have historically been more important in explaining stock returns than the macroeconomic variables. Bekaert and Harvey (1997) examine volatility dynamics among 20 emerging stock markets and Angela Ng (2000) tests volatility spillover effects from Japan and the U.S. to the Pacific-Basin. Most of the research has only concentrated on mature and developed stock markets. There are comparatively few studies on emerging stock markets.

Usually, the co-movement of stock returns is widely discussed not only in academics but also in the finance industry. It provides valuable information for international investors who are looking to take advantage of diversified portfolios. A number of empirical studies have been conducted to investigate international asset return co-movements, but they all fail to find evidence of a trend in stock return co-movements across countries. Nevertheless, the co-movement of returns is much less clear than volatility. Volatility is measured as “fear” that is usually spread out quickly and easily across countries, and then such widely spread fear contributes to the co-movement of international stock markets.

In this chapter, we investigate volatility dynamics of stock returns to capture co-movements across world stock markets. A dynamic factor model is designed to decompose stock return volatilities into three orthogonal factors: the world factor, the region factor and the local factor,

which are assumed to capture all the variation of return volatilities. Fourteen countries are included in our empirical study in order to cover both developed stock markets and emerging stock markets. Those countries belong to four regions: North America, Europe, Asia and Latin America. The main goal of this chapter is to examine considerable volatility co-movements across stock markets and explain how much of the co-movements can be accounted for by the world factor, the region factor and the local factor in each country.

When it comes to measuring volatilities, the VIX (Chicago Board Options Exchange Market Volatility Index) is a popular measure of the implied volatility of S&P 500 index options. It was first introduced by Robert E. Whaley (1993) and first-ever traded on March 26, 2004 on the CBOE Future Exchange. The formula to calculate VIX uses a kernel-smoothed estimator that takes as inputs the current market prices for all out-of-the-money calls and puts for the front month and second month expirations. The goal is to estimate the implied volatility of the S&P 500 index over the next 30 days. Over its history, the VIX has acted reliably as a fear gauge. High levels of VIX are coincident with high degrees of market turmoil, whether the turmoil is attributable to stock market declines, the threat of war, unexpected changes in interest rates, or any number of other newsworthy events.

However, the VIX is implied volatility which is obtained from an option pricing model, such as Black-Scholes. The VIX reading completely depends on the selection of pricing models. Hence, the VIX is a subjective measure and differs from historical volatility. In this study, we base the measure of volatility on known past returns of stock indexes. We use the log of monthly sample variance of daily stock returns to measure volatility. To compare with the VIX, following

plots are drawn over the period 1993 to 2009. The correlation between the VIX and our measure of volatilities is around 0.66.

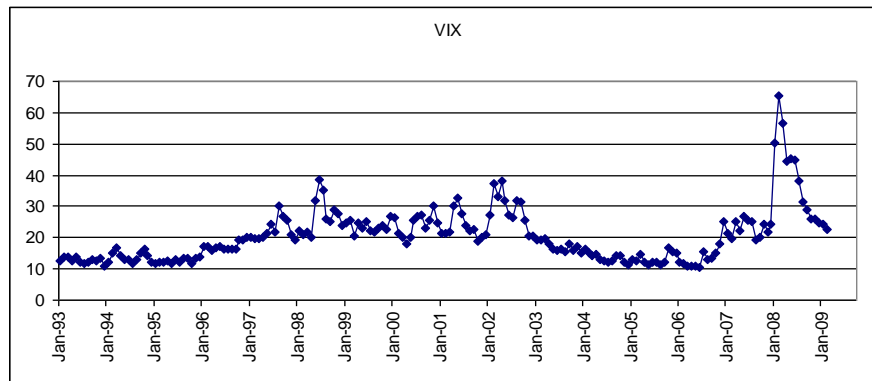


Figure 1: VIX over time during 1993 to 2009

*Notes:* VIX reading is monthly CBOE Volatility Index (VIXCLS). Data source: Federal Reserve Economic Data, Federal Reserve Bank of St. Louis.

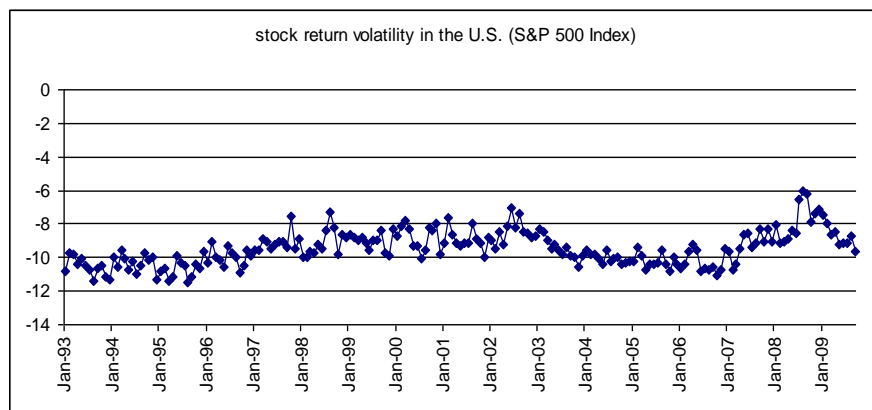


Figure 2: Historical stock return volatility in the U.S.

*Note:* The measure of stock return volatility in the U.S. is log of monthly sample variance of daily returns of S&P 500 index.

A dynamic factor model is implemented in this study to capture the co-movements of stock return volatilities in the world stock markets. The stock return volatilities are decomposed into three orthogonal factors: the world factor, the region factor and the local factor (idiosyncratic

component), which are designed to capture all fluctuations of volatilities. Otrok and Whiteman (1998) use a Bayesian dynamic latent factor model to analyze the business cycle. Posterior distributions of parameters and latent factors are analyzed by the Markov Chain Monte Carlo methods. We apply the similar methodology to estimate unobserved factors and all parameters for our model.

We successfully capture the common factors which are able to account for more than 50% variation of the stock return volatility for most of countries. The world factor unveils a significant worldwide co-movement that has a big impact on North American and Latin American markets; nevertheless, the region factor is more important in explaining fluctuations in European and Asian stock markets. It shows that when the volatility appears high, the world factor turns to be more important in accounting for the interdependence and co-movement among stock markets over the world.

## **2.2 Empirical Framework**

### **2.2.1 Data**

The raw data employed in this paper are daily stock indexes prices in terms of US dollars from the Datastream. The stock indices are from 14 countries over period 1993 January-2009 September<sup>1</sup>. Stock indexes returns are used to calculate the monthly volatility which is not observed. Our measure of volatility is the log of monthly sample variance of daily returns.

---

<sup>1</sup> Stock indices used in 14 countries are: U.S. (S&P 500), Canada (S&P/TSX), UK(FTSE ALL SHARE), Germany (DAX 30 PERFORMANCE), France (S&P FRANCE BMI), Italy (S&P ITALY BMI), HongKong (HANG SENG), South Korea (KOREA SE COMPOSITE), Taiwan (TAIWAN SE WEIGHTED), Singapore (FTSE ST ALL SHARE L), Argentina (ARGENTINA MERVAL), Brazil (BRAZIL BOVESPA), Chile (CHILE GENERAL) and Mexico (MEXICO IPC).

14 countries studied in this paper are divided into four regions: North America, Europe, Asia and Latin America. The classification of countries is showed at Table 1.

Table 1: Classification of 14 countries

<b>World</b>	<b>Region</b>	<b>Country</b>
Common	North America	
		US
		Canada
	Europe	
		UK
		Germany
		France
		Italy
	Asia	
		Hong Kong
		South Korea
		Taiwan
		Singapore
	Latin America	
		Argentina
		Brazil
		Chile
		Mexico

*Notes:* The selection of countries depends on influence of the stock markets and also availability of data. We intended to include the same number of countries for each region. But, North America is an exception since there are only two influential markets in that region.

### 2.2.2 Model Setup

The goal of this study is to investigate dynamics of the co-movement of volatility in global stock markets. In order to capture such co-movement, we assume volatility is an observed variable by using a proxy measure based on stock index prices data. It is also assumed that there exist a worldwide co-movement and a regional co-movement that can explain the certain amount of variation for each market.

To satisfy the assumptions above, we apply the dynamic factor model to decompose volatility of stock returns into two unobserved and orthogonal common factors: the world factor



and region factor. The world factor is assumed to explain a worldwide co-movement and the regional factor is accounted for a regional co-movement. The local shock which is not spread out to other countries is captured by an idiosyncratic component. All three components in the model together are assumed to capture all the variation of volatility for each stock market.

Take country  $i$  for example,  $y_{it}$  denotes volatility in country  $i$  at time  $t$ , and  $f_t^w$  and  $f_t^r$  denote the world factor and region factor at time  $t$ .  $\lambda_i$  is the factor loading for country  $i$  and  $\mu_{it}$  denotes the idiosyncratic component at time  $t$  for country  $i$ .  $a_i$  is the intercept. It is assumed that all factors and idiosyncratic components follow AR (2) process. The model is structured as follows:

$$y_{it} = a_i + \lambda_{i1}f_t^w + \lambda_{i2}f_t^r + \mu_{it}$$

Subject to:

$$f_t^w = \phi_1^w f_{t-1}^w + \phi_2^w f_{t-2}^w + \varepsilon_t^w$$

$$f_t^r = \phi_1^r f_{t-1}^r + \phi_2^r f_{t-2}^r + \varepsilon_t^r$$

$$u_{it} = \varphi_{i1}u_{i,t-1} + \varphi_{i2}u_{i,t-2} + e_{it}$$

Where:

$$\begin{bmatrix} \varepsilon_t^w \\ \varepsilon_t^r \\ e_{it} \end{bmatrix} \sim N \left( \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_w^2 & 0 & 0 \\ 0 & \sigma_r^2 & 0 \\ 0 & 0 & \sigma_i^2 \end{bmatrix} \right)$$

In the matrix notation, the model can be demonstrated below in a general case.

In the baseline model, the dependent variable is volatility of stock indices returns in N countries and there are K unobserved factors which are well suited to capture the variation of volatility in stock markets. For N observables at time t:

$$y_t = a + \Lambda f_t + u_t$$

$\begin{matrix} N \times 1 & (N \times 1) & (N \times K) & (K \times 1) & (N \times 1) \end{matrix}$

Subject to:

$$f_t = \Phi_1 f_{t-1} + \Phi_2 f_{t-2} + \varepsilon_t$$

$\begin{matrix} (K \times 1) & (K \times K) & (K \times 1) & (K \times K) & (K \times 1) & (K \times 1) \end{matrix}$

$$u_t = \Psi_1 u_{t-1} + \Psi_2 u_{t-2} + e_t$$

$\begin{matrix} (N \times 1) & (N \times N) & (N \times 1) & (N \times N) & (N \times 1) & (N \times 1) \end{matrix}$

$$\begin{bmatrix} e_t \\ \varepsilon_t \end{bmatrix} : N \left( 0, \begin{bmatrix} \Sigma_{ee} & 0 \\ 0 & \Sigma_{\varepsilon\varepsilon} \end{bmatrix} \right)$$

$\begin{matrix} (N+K) \times 1 & & & & & \begin{matrix} \Sigma_{ee} \\ (N \times 1) \\ \Sigma_{\varepsilon\varepsilon} \\ (K \times 1) \end{matrix} \end{matrix}$

Where  $y_t$  denotes volatility of stock indices in N countries discussed above, and  $f_t$  denotes unobserved factors and  $\Lambda$  stands for the factor loading matrix.  $u_t$  is the idiosyncratic component (or error term) for each observable. Factors and idiosyncratic components follow autoregressive processes of order p and q.  $\Psi, \Phi$  are both diagonal which implies that all factors and idiosyncratic components only depend on its own lagged values. Vector a is an Nx1 vector of constants.

In more details, for example, in country i, the world factor, region factor, and idiosyncratic component together contribute to all the variation of stock volatility. Some occasions that affect all countries in the world impact country i through the world factor, and fluctuations that only spread out within the region influence country i by the regional factor. Some local shocks, such

as monetary shocks of the individual government, which merely affects other countries, only has impact on country  $i$  through the idiosyncratic component. The dynamics of volatility assumed in this model is simple: a shock in Asia, for example, if goes to all other markets in the world, then such worldwide co-movement caused by this shock will be captured by the world factor. If this Asian shock only spreads out across Asian countries, then it will be explained by the regional factor (i.e. the Asian factor in this case).

### **2.2.3 Computational Procedure**

Otrok and Whiteman (1998) used a method based on development in the Bayesian literature to compute dynamic factor models with large data sets. A simple structure can be used to determine the conditional (normal) distribution of the factors given the data and the parameters of the model. Then it is straightforward to generate random samples from this conditional distribution, and such samples can be employed as stand-ins for the unobserved factors. Because the full set of conditional distributions is known-parameters given data and factors, factors given data and parameters-it is possible to generate random samples from the unknown parameters and the unobserved factor by using a Markov-Chain Monte Carlo (MCMC) procedure. This sequential sampling of the full set of conditional distributions is known as "Gibbs sampling" (Siddhartha Chib and Edward Greenberg, 1996; John Geweke, 1996, 1997).

The practical benefit of this procedure is that it can easily be applied to a large cross section of countries. Classical maximum likelihood methods generally are difficult to apply to a problem with large dimensions. However, the difficulty with sampling from the conditional distribution of the factor arises because of a long time series. In our particular case, given monthly volatility in 14 countries from 1993 to 2009, it is difficult to handle the computational burden. Therefore, we

turned to use Kalman Filter to estimate unobserved factors and keep using the Gibbs-sampling for estimating parameters. See computational details in Appendix.

## 2.3 Empirical Results

### 2.3.1 Model Estimation

As discussed in last session, the co-movement of stock returns has been widely discussed, but a clear return co-movement has not been found in the literature. To verify this result, we first follow the existing literature by applying stock returns into the baseline model described in the section 2.2. The result is consistent with the literature that proportions of stock returns variation captured by the world and regional factors are very small. There does not exist a clear co-movement of stock returns. Figure 3 shows the worldwide co-movement of returns which is explained by the world factor in the model. As we predicted, the return co-movement is unclear and it is hard to find useful information through such a volatile movement trend to reach valuable conclusions.

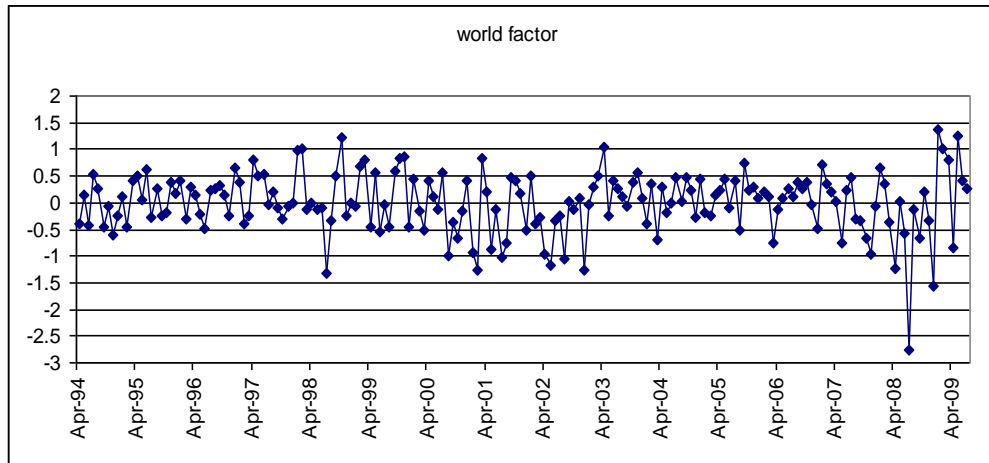


Figure 3: The world factor for stock indices returns

*Note:* The world factor is estimated from the stock returns model, in which stock returns, as the observable, are decomposed into three orthogonal components: the world factor, regional factor and local factor.

Instead of stock returns, the main interest of this study is to investigate volatility which is considered to exhibit more tight co-movements than returns across stock markets. Compared to returns, volatility is relatively persistent and widely believed to be predictive. It is reasonable to assume that there exists a clear worldwide or regional co-movement of volatility across stock markets by decomposing volatility into common factors. It is also interesting to investigate that how much of the variation of stock volatility can be accounted for by the worldwide and regional co-movement.

By applying volatility data into the model, we estimate three unobserved factors: the world factor, the region factor and the local factor, which are designed to capture all the variation of volatility for each stock market. Figure 4 shows the world factor obtained in the volatility model. Compared to the world factor from the return model as showed in Figure 3, the movement of the world factor in Figure 4 is more stable and is able to give a clear picture of historical worldwide fluctuations occurred on the world stock markets. For instance, when the Asia crisis occurred in 1997-98, the fear of a global downturn of stock returns quickly spread out internationally which contributed to the worldwide co-movement at that time, and such co-movement is captured by the world factor during 1997-98 as showed in Figure 4. Another typical example is the subprime financial crisis in 2008 that was originated in the U.S. and soon affected the rest of the world. Such worldwide chaos is also captured by the world factor.

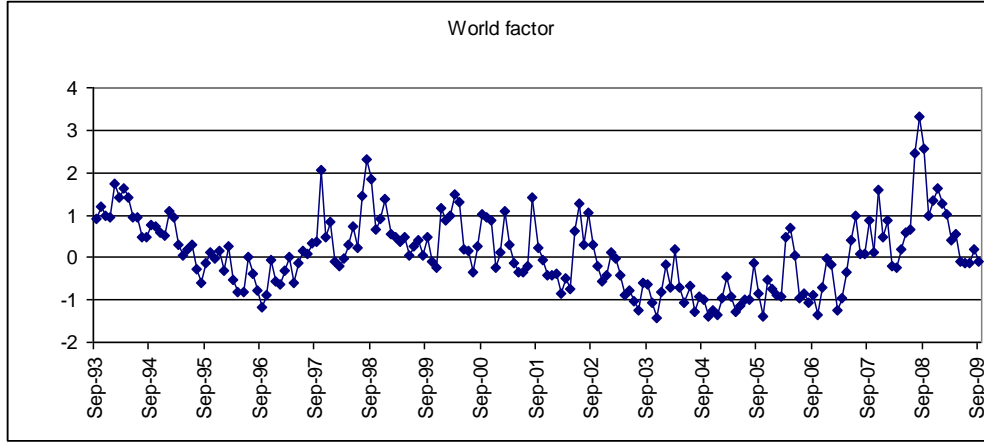


Figure 4: The world factor for stock indices return volatility

*Note:* The world factor is estimated from the stock returns volatility model, in which stock return volatility is the only observable that is decomposed into the world factor, regional factor and local factor.

Nevertheless, the baseline model estimation only gives a simple idea that how the co-movement of volatility changes over time. In the next session, we provide historical variance decomposition to analyze that how much proportion of variation of volatility in each market can be explained by the world, region, and local factor over time.

### 2.3.2 Historical Volatility Growth Decomposition

Since the dynamic factor model is designed to decompose the observed variable into several orthogonal factors, variance of the observed variable is the sum of variance of all factors including the error term (or idiosyncratic component). The ratio of variance of each factor to variance of the observed variable can be explained as shares by which such factor is attributable to variation of the observed variable.

On the research of international business cycle, variance decomposition is explored to measure the relative contributions of the world and regional factors to variation of macroeconomic fundamentals in each country by estimating the share of the variance accounted

for by each factor. With the assumption of orthogonal factors, the fraction of variation due to the factor  $j$  in country  $i$  is:

$$\frac{\lambda_{ij}^2 \text{var}(f_j)}{\text{var}(y_i)} \quad \text{where } \lambda \text{ is the factor loading, } f \text{ is the factor and } y \text{ is the observable.}$$

$i=1,2,\dots,N$ , denotes countries.  $j$  represents the world or regional factor. For instance,  $i=1$  and  $j=1$ ,  $\lambda_{11}$  means the world factor loading for country 1. With this method to calculate variance decomposition, it only provides a constant share of the variance explained by each factor.

In this study, we implement a historical volatility growth decomposition that is different from the existing literature in order to achieve time-varying variance shares. From the baseline model described in the section 2.2, it can be derived that

$$y_{it} - y_{i,t-1} = \lambda_{i1} (f_t^w - f_{t-1}^w) + \lambda_{i2} (f_t^r - f_{t-1}^r) + (u_{it} - u_{i,t-1}) \quad \text{for country } i.$$

The equation above indicates that volatility growth in country  $i$  equals the sum of growth of factors (including the idiosyncratic component). In order to remove the effect of seasonality, we imply the year-over-year growth which is measured by log difference between the same months' value in this year and one year before. The fraction of volatility growth at time  $t$  in country  $i$  due to the factor  $j$  can be derived as below:

$$\frac{\lambda_{ij} (f_{jt} - f_{j,t-1})}{y_t - y_{t-1}}$$

The results on the historical volatility growth decomposition are showed in the Figure 5 – 8. Figure 5 describes the year-over-year growth of volatility and all factors in North American

stock market. In Figure 5, the growth of regional factor is not included. Because in North America, the regional factor growth fails to explain any of the volatility growth. The growth of regional factor was almost equal to zero over time. Hence, we exclude it to make the figure show a clearer picture of other three growth rates.

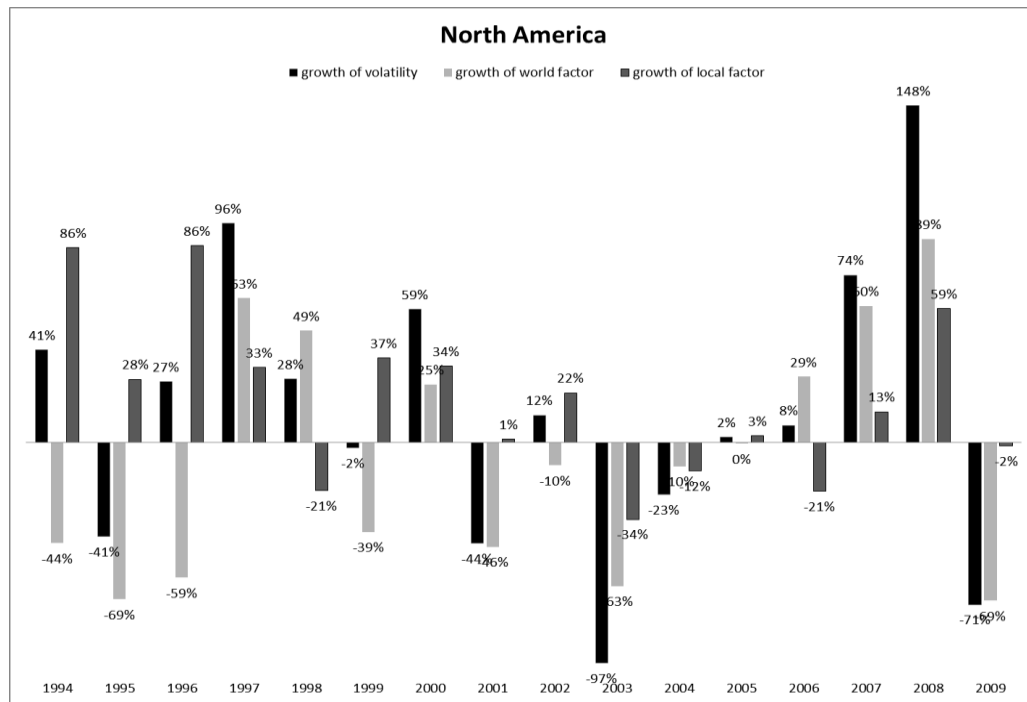


Figure 5: Historical volatility growth decomposition in North America

*Notes:* The growth is measured by the log difference. The growth of volatility is the sum of growth of world factor, regional factor and local factor. Figure 5 doesn't show the growth of regional factor because the estimated regional factor for North America mostly equals zero over time.

In North America, the world factor is able to account for most portion of volatility growth, especially when the stock markets are experiencing high volatility, for instance, the subprime financial crisis in 2008. When crises take place, the world factor becomes more important in explaining the fluctuation of volatility. Nevertheless, before 1996 the importance of the world factor was much less obvious than after 1997 until present.



The regional factor for the U.S. and Canada fail to capture a clear regional co-movement of stock return volatility. The reason could be that stock markets in the U.S. and Canada are highly commoved, and such co-movement has completely contributed to the world factor especially when the U.S. stock market is dominant in the world. Hence, there is no commoved variation of volatility left between the U.S. and Canada that can be explained by the regional factor.

Figure 6 gives results on the historical volatility growth decomposition in European stock markets.

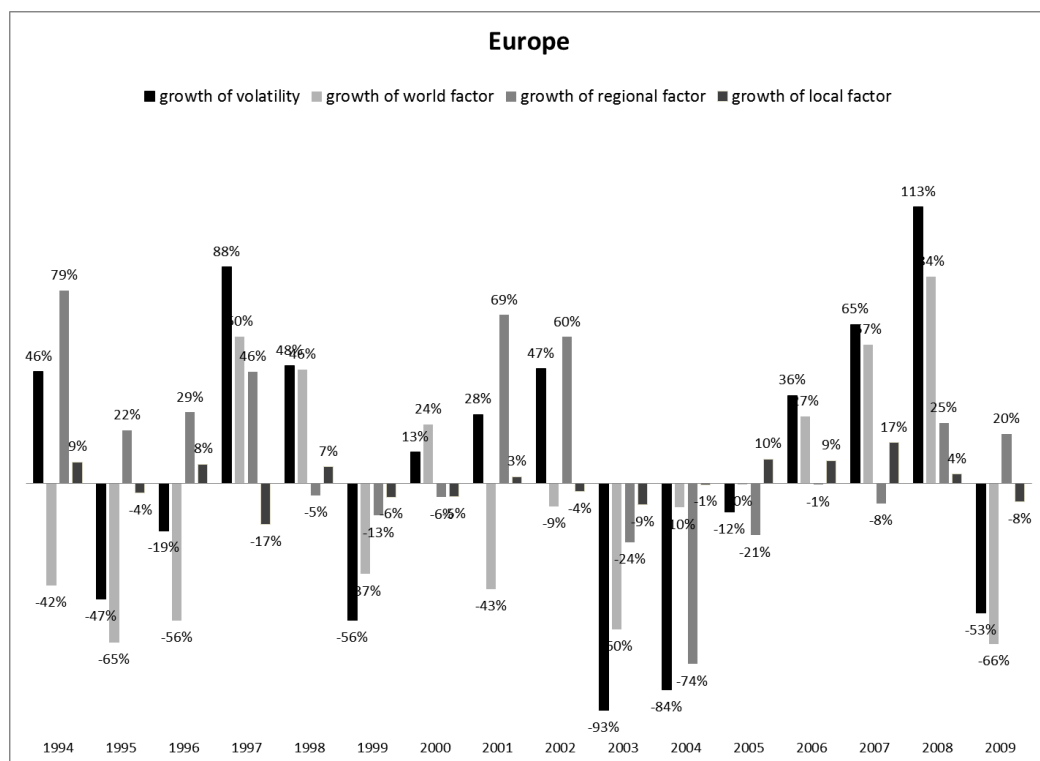


Figure 6: Historical volatility growth decomposition for Europe

*Note:* See notes to Figure 5.

Unlike the North American stock market, the regional factor plays an important role to explain growth of volatility in the European markets. It reveals an obvious regional co-

movement across European stock markets and such regional co-movement does not largely spread out to other markets outside to form a worldwide co-movement. This finding is in line with widely agreed views on European markets. The unique currency and monetary policy could together contribute to a clear regional co-movement across the stock markets in Europe.

Figure 6 also shows that the world factor growth was coincident with volatility growth in Europe prior to 1996. In other words, the world factor played an important role to explain volatility variation in Europe during that time period. It is interesting to check that if the world stock market was dominated by Europe than the U.S. before 1996. When a big turndown occurred in European stock markets during 2001, the stock volatility growth was in part explained by the world factor, and the world factor at the time could be resulted from the internet bubble bursting. More importantly, a large portion of volatility growth during 2001 was accounted for by the regional co-movement which could be due to the new introduction of euro.

The peak of volatility growth in Europe happened in 2008, apparently caused by the subprime financial crisis. For this chaos, most of fluctuation in European stock markets was contributed by the world factor, especially during the recovery period. Furthermore, volatility growth at peaks in Europe appears to be higher than that in North America, which indicates that fears of stock downturn are multiplied more in Europe than in North America. In other words, European stock markets are substantially sensitive to big fluctuations around the world.

Figure 7 shows the historical volatility growth decomposition for Asian stock markets.

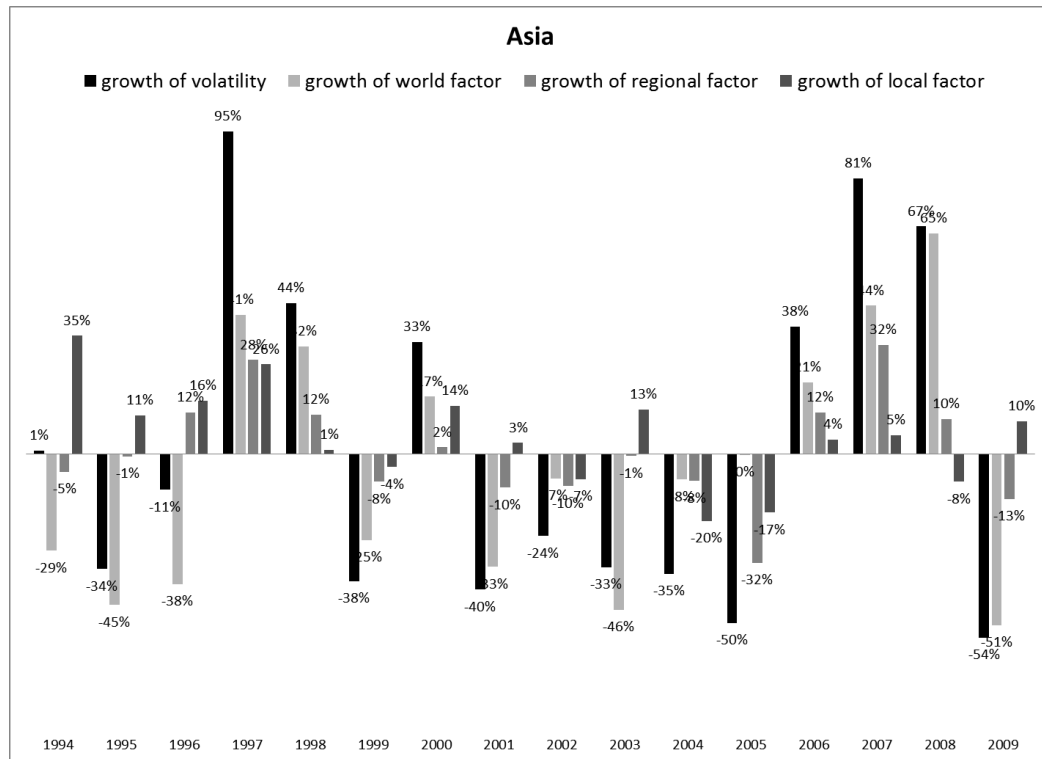


Figure 7: Historical volatility growth decomposition for Asia

*Note:* See notes to Figure 5.

Compared to the world factor, volatility growth in Asian stock markets is driven more by the regional factor. Some studies on this topic have achieved the conclusion that Asian stock markets fluctuations are mainly due to intra-regional contagion effects. Our research shows the consistent results with such conclusion.

When the Asian crisis occurred in 1997, the regional factor along with the local factor accounted for a big portion of volatility variation in Asian markets and the world factor was not the dominant factor to determine the volatility growth even with such worldwide chaos. The reason could be that, as the epicenter, fluctuation of Asian stock markets created fears that weren't completely shared by the rest of the world. The fears definitely spread out to other regions and then created a global downturn in international stock markets, but more variation

was remained within Asia. Such remaining fluctuation was captured by the regional factor. But when the subprime financial crisis happened in 2007, it affected Asian stock markets by a large amount. Asian markets were dominated by the world factor during that time. Hence, a conclusion can be reached that Asian stock markets don't have as much influence on the international stock market as it does on Asia.

In Latin American stock markets, results are consistent with existing studies that major proportion of stock index variance is contributed by foreign stock markets. Figure 8 reveals the importance of the world factor in explaining volatility growth in Latin American stock markets.

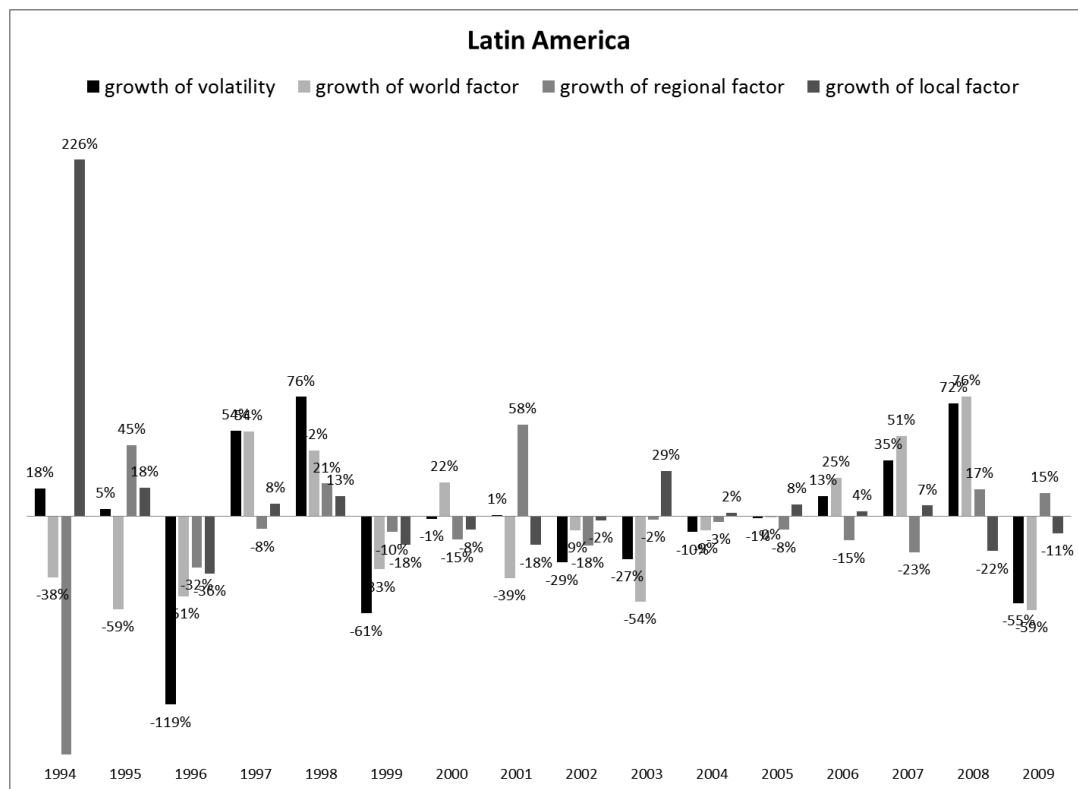


Figure 8: Historical volatility growth decomposition for Latin America.

Note: See notes to Figure 5.

Most of crises originated in Latin America are not shared by the rest of the world. 1994 financial crisis occurred in Mexico is a typical example. According to the Figure 8, a big fluctuation appears in 1994 due to the Mexican crisis, but almost all of volatility change was explained by the regional and local factor. The world factor barely had impact on Latin American stock market at the time. The recovery in Latin America after crises is usually doing better than the world average which is contributed mostly by the regional stabilization. In addition, during 2004 to 2006, the regional factor growth appeared to be very stable around the center of zero, which represents a good time period of the regional stabilization for Latin America. Such regional stabilization could be a consequence of high growth in GDP during that time in Latin American countries.

To give a clearer picture on proportions of volatility growth that can be explained by different factors, we take average on growth of volatility and factors for each region over time. The results are showed in Figure 9.

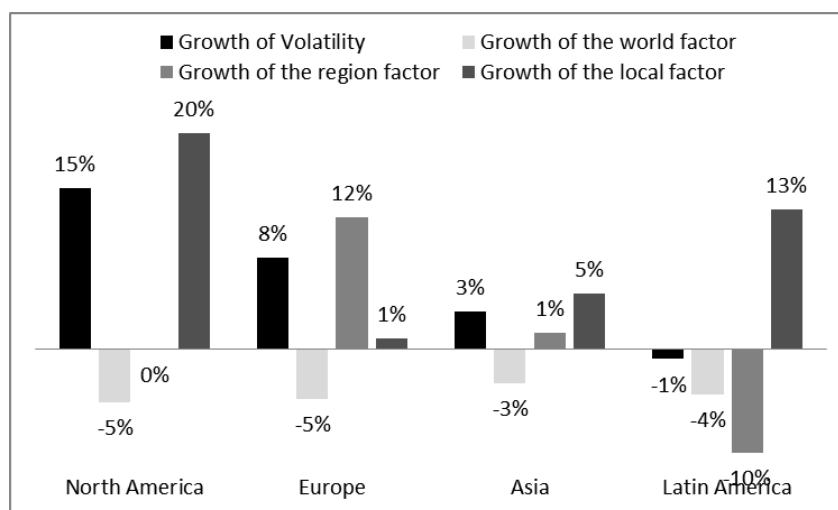


Figure 9: Growth of volatility and factors for all regions

*Notes:* Bars represent regional averages on growth over the entire sample period. For each region, the average growth of volatility equals the sum of average growth of the world factor, region factor, and local factor.

Developed stock markets, such as North America and Europe, are more volatile than less developed markets like Asia and Latin America. The year-over-year growth of volatility on average in North America is around 15% compared to 3.4% for Asia. The world factor has been negatively influencing all stock markets across the world. In other words, stock markets would be more volatile if there doesn't exist a worldwide co-movement. Such worldwide co-movement that helped to stabilize world stock markets could be contributed by international capital mobility, risk sharing and so on. The region factors play important roles in stock markets of Europe and Latin America, although in the different directions. In Europe, the regional factor makes stock markets more volatile and it is the main force of the stock volatility growth. Nevertheless, the regional factor helps make Latin American stock markets more stable. The favorable regional factor in Latin America could be considered as the regional stabilization due to the highly growing GDP in major Latin American countries.

Figure 10-13 show the separate analysis for each region. At each table, it first gives overall results on the year-over-year growth on volatility and factors, and then reveals how it changes when the stock markets in each region are experiencing high volatility.

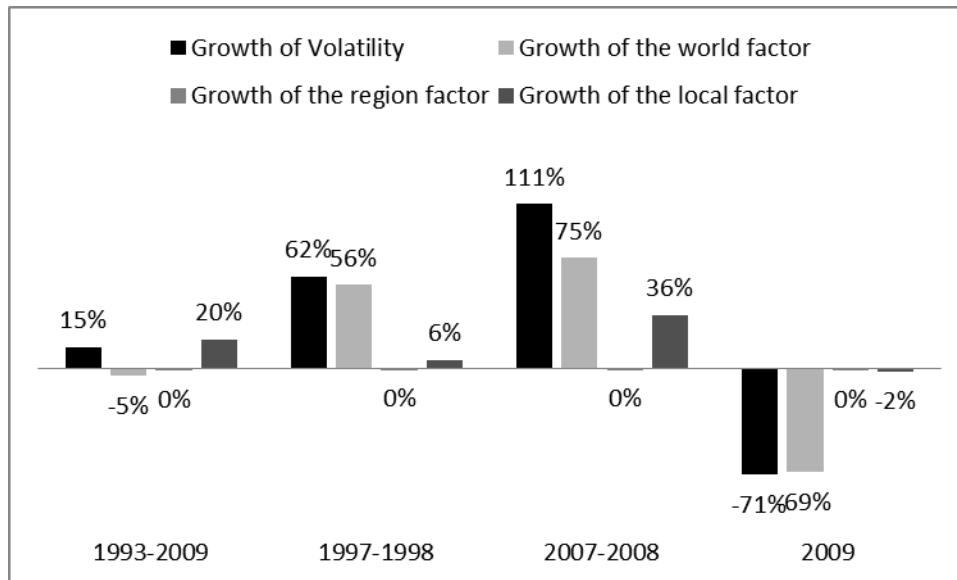


Figure 10: Average growth of volatility and factors in North America

*Notes:* Bars represent average growth in North America over different time periods. For each time period, the average growth of volatility equals the sum of average growth of world factor, region factor, and local factor.

When financial crises happened, the world factor became a dominant factor in explaining the fluctuation of stock markets in North America. The region factor was never important for North America. The reason could be that there are only two countries in the sample, i.e. the U.S. and Canada, that belong in North America and their stock markets are highly correlated. Such correlation is coincident with the worldwide co-movement. Hence, the regional co-movement between U.S. and Canada has been captured by the world factor. Even though the financial crisis was originated in Asia in 1997, it quickly spread out to outside countries and then formed a worldwide fluctuation. Such worldwide co-movement was explained by the world factor which dominated North American stock markets at the time. But for the subprime financial crisis originated in the U.S., even with the dominance of the world factor, the local factor was able to explain roughly one third of variation of stock volatility. It is in part because the U.S. and

Canada reacted to the crisis differently on some level and such difference contributed to the importance of the local factor for North American stock markets during 2007-08.

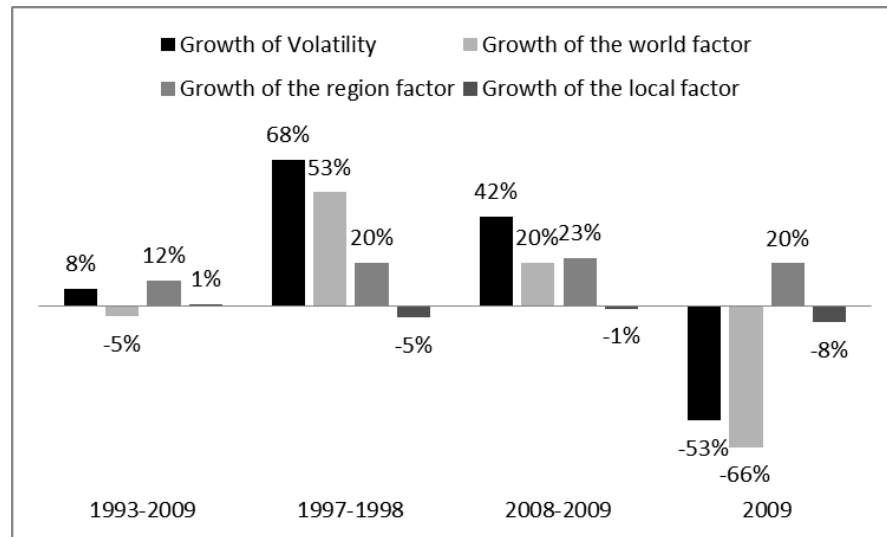


Figure 11: Average growth of volatility and factors in Europe

*Note:* See notes to Figure 10.

The regional factor appears to be an important factor to explain the long-term growth trend of volatility in European stock markets as showed at Figure 11. When financial crises happened across the world, European stock market acted differently from the rest of the world on a substantial level. Such different reactions to financial crises were showed by the regional factor, which accounted even more for volatility growth during crises than at normal times. After the economy started recovering in 2009 from the subprime financial crisis, the stock market in Europe had been stable given a volatility growth of -53%. However, volatility in European stock markets during that time period was decreased at a slower pace than the global stock markets. The regional factor has driven stock markets in Europe to be more volatile, without which the markets could have performed better. When majority of countries in Europe joined the union in order to make their economies stronger, it makes easier for them to get into the same crisis and



harder to recover. Due to the high correlation across European countries, the local factor is never important in explaining fluctuation of stock markets in this region.

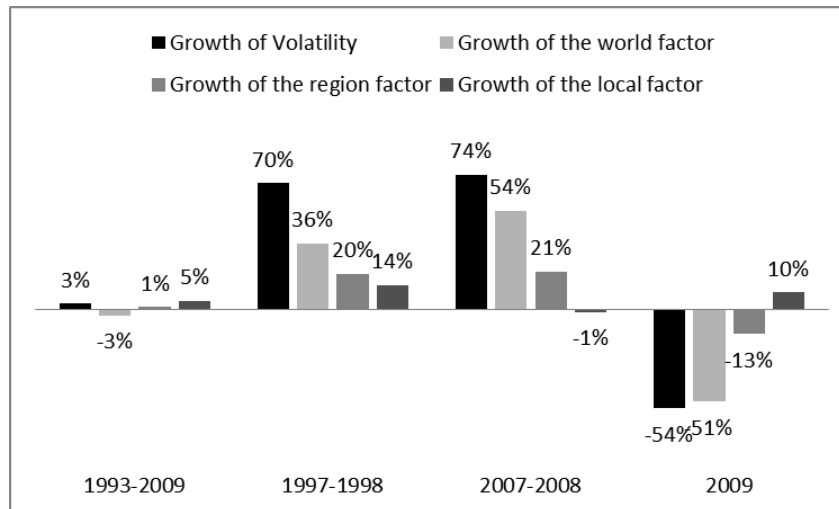


Figure 12: Average growth of volatility and factors in Asia

*Note:* See notes to Figure 10.

Overall, Asian stock markets are less volatile than developed stock markets. The average volatility growth in Asia over time is only 3.38%. The local factor has been contributing a large portion of variation in Asian stock markets. Nevertheless, the world factor helped stabilize the markets except for the crises time. Asian stock markets have benefitted largely from the global co-movement. When the Asian Crisis occurred in 1997, a worldwide fluctuation in stock markets was created by fears spreading out quickly to all other markets. That shared worldwide fluctuation was explained by the world factor which was responsible for a large portion of volatility growth for Asian stock markets at the time. However, part of the variation caused by the crisis remained in the region. The remaining variation shared by the whole region was captured by the regional factor, and when each country in Asia reacted differently, the unique variation only happened in particular country was accounted for by the local factor. During the

recovery, both of the world and regional factors contributed to stabilize Asian stock markets, whereas the local factor moved in an opposite way. The negative effect from the local factor could be attributed by monetary policy shocks from the local governments, changes in expectation of the local stock markets, and etc.

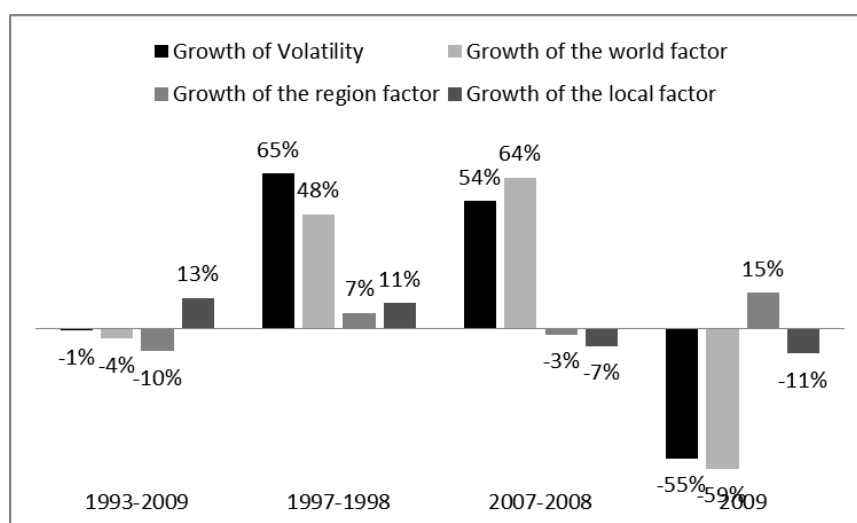


Figure 13: Average growth of volatility and factors in Latin America

*Note:* See notes to Figure 10.

The long term growth of volatility in Latin American stock markets turns out to be the smallest among all of the stock markets. Other than the local factor, the world and regional factors both helped stabilize stock markets in Latin America. The big decline in growth of the regional factor could be resulted from the regional stabilization, especially from 2004-2006. When worldwide financial crises occurred, Latin American stock markets were also very volatile, like all other markets. Most of volatility growth in Latin America during the crises was contributed by the world factor, which demonstrates the dependence of Latin American stock markets on other countries. But the local stock markets were also largely influenced by the local factor which explained some specific local variation. During the Asian Crisis, the local factor in

Latin America worsened the stock markets by increasing the volatility growth of roughly 10%. But during the recovery from the subprime financial crisis, the local factor contributed to slow the growth of volatility by around 10%, which could be resulted from steadily growing economies in Latin America and less reliance on foreign markets.

## **2.4 Conclusions**

The main goal of this research is to capture unobserved common factors which should be able to explain a big portion of variation in world stock markets. Instead of using the implied volatility, such as VIX, we measure the volatility based on the observed past returns of stock indexes. A dynamic factor model is designed to decompose stock return volatility into three orthogonal factors: the world factor, the regional factor and the local factor, which are assumed to be well suited for explaining all the variation of volatility. Fourteen countries are included in our empirical study in order to cover both developed and emerging stock markets.

Based on the empirical results, we successfully capture common factors which are able to account for more than 50% of variation of volatility for most of countries. The world factor turns out to be significant for North American and Latin American markets; nevertheless the regional factor is important for Europe and Asia. It shows that when volatility becomes high, the world factor becomes more important in explaining interdependence and the co-movement among stock markets over the world. The underlying dynamics is that when one stock market is experiencing high fluctuation, it generates fears which can spread out quickly to the rest of the world. Hence, a worldwide co-movement across world stock markets is formed and such co-movement is captured by the world factor in our model. The regional co-movement is clearly

observed in Europe and Asia. The reason could be traced back to the intra-regional trade and investment and tight tie between markets in these two regions in terms of the unique currency or common monetary policies.

### **3. Spill-over effects among world stock markets**

#### **3.1 Introduction**

In Chapter 2, we investigate the co-movements on global stock markets. We are able to reach the conclusion that there exist clear world-wide and regional co-movements of stock return volatilities across different markets. The next interesting question that comes to mind is that despite the corresponding movements among markets, whether or not there exists specific linkage between two different countries or regions. Some would say that when the U.S. stock market sneezes, all other countries get a cold. If such assumption is true, has the dominance of the U.S. shifted as global stock markets are getting more integrated? It is also interesting to investigate spillovers between emerging stock markets since emerging markets have become more independent and decoupling from developed markets due to the development of their economies and financial systems.

Since spillovers analysis provides valuable information for international investors who are looking to take advantage of portfolio diversification, the study in this field has attracted significant attention. However, most of the exiting literature used GARCH models and stochastic volatility models to realize the unobserved stock volatility (see more detail in Chapter 1) which results in dependence of empirical findings on the model selection. On the other hand, the existing empirical studies on spillovers mostly use high frequency data, like daily stock prices. It eliminates the intuition of such studies for long term investors who are looking for relatively stable correlation between different markets in the long run to help them benefit from the potential diversified risk.

In this Chapter, we keep the same data structure as the Chapter 2 and follow the same model framework. But in order to address the problem of volatility spillovers, we modify the baseline model by adjusting transition equations to realize spillover effects of one country or a group of countries on others. Furthermore, we analyze financial integration effects on world stock markets by extending the time horizon to 1967 and cutting down to 9 countries due to lack of data for some countries.

## **3.2 Spill-over Effects Analysis**

### **3.2.1 Spillovers from the U.S. to the rest of the world**

In the section 2.3.2, it shows that the world factor have been playing an important role in explaining fluctuations in each stock market. It is interesting to investigate that what the driving force of the world factor is. One would undoubtedly guess the U.S. stock market has been dominant in the global stock market. Several empirical studies show that the U.S. stock market achieved market dominance in the last century. The U.S. stock market increased its weighting to around 47% of the world's total, and it performed more favorably than the rest of the world's markets. This occurred for several reasons. The U.S., compared to any other countries, had larger investment in physical and human capital, greater technology and productivity growth. With its huge investment demand and technological superiority, the U.S. equity market was a worldwide leader.

However, there has been growing concerns in the past decades that the U.S. capital markets have been losing market shares to overseas competitors and the position of dominance held by the American stock market is waning. Especially after globalization took effect in the mid-1980s, the fast growing international trade among countries has resulted in closer relations than ever

between different economies across the world. When each country is sharing its contribution to the world economy, it became difficult for the U.S. to keep a dominant position. Nevertheless, some economists argued that the U.S. equity market is still served as a key funding source, not only for the U.S., but also for foreign corporations. As a major global financial center, fluctuations of the U.S. economy are still largely affecting the rest of the world. It is interesting to conduct an empirical study by using recent data to investigate whether or not the U.S. stock market is still playing a major role in determining the worldwide co-movement of the global stock volatility.

To address the problem, we modified the baseline model described in Chapter 2 in the following ways. First, in the measurement equation, the world factor doesn't include the U.S. impact. In other words, the U.S. is excluded in the sample of countries, or the observable  $y_t$  becomes a  $13 \times 1$  vector, instead of  $14 \times 1$ . Secondly, in the transition equation of the world factor, we add lagged U.S. stock return volatility as a factor to affect the world factor's motion. By making such changes in the modified model, the coefficients of the lagged U.S. stock return volatility get to indicate the impact of U.S. stock market on the global stock volatility co-movement.

The modified model can be written as follows:

$$y_{it} = a_i + \lambda_{i1} f_t^w + \lambda_{i2} f_t^r + u_{it}$$

Subject to:

$$f_t^w = \phi_1 f_{t-1}^w + \phi_2 f_{t-2}^w + \phi_3 f_{t-1}^{us} + \phi_4 f_{t-2}^{us} + \varepsilon_t^w$$

$$f_t^r = \phi_1^r f_{t-1}^r + \phi_2^r f_{t-2}^r + \varepsilon_t^r$$

$$u_{it} = \phi_{i1} u_{i,t-1} + \phi_{i2} u_{i,t-2} + e_{it}$$

Note that  $y_{it}$  denotes the observed stock return volatility in country  $i$  at time  $t$ ,  $i=1,2,\dots,11$ . The U.S. is not included in the sample. In the world factor's law of motion, the current world factor not only depends on its own lagged values but also the lagged U.S. volatility (or the US factor).

The results show that coefficients of the US factor (i.e.  $\phi_3, \phi_4$ ) are both statistically significant with values of 2.1145 and 1.4577. Compared to coefficients of the lagged world factor ( $\phi_1 = 0.0122$  and  $\phi_2 = 0.0021$ ), we can reach the conclusion that the U.S. has a substantial and significant impact on the world factor. It shows that the fluctuations in the U.S. stock market have been contributing largely to the worldwide co-movement, and the U.S. stock market is still holding a dominant position on the global stock market, at least during the last two decades and among eleven countries in our sample.

### 3.2.2 Spillovers from the U.S. to Asian stock markets

It has been widely accepted that the U.S. stock market has impacted to a high degree on Asian stock markets. It is in part because that majority of Asian countries have the U.S. as one of their major trading partners and most of their currencies are tied to the US dollar. The fast growing international trade between the U.S. and Asia, and little exposure to the exchange rate risk for Asian investors together result in high spillovers from the U.S. to Asian markets.



In Section 3.2.1, we managed to show that the U.S. market spreads out its fluctuation to the rest of the world through the world factor. Such transmission mechanism partly explains the linkage between the U.S. and Asian stock markets. But a natural question would be asked that if there exists a direct impact of the U.S. on Asian stock market besides the spread-out mechanism through the worldwide co-movement.

To model the spillovers from the U.S. to Asian stock market, we redesign the Asian regional factor's law of motion as follows:

$$f_t^A = \phi_1 f_{t-1}^A + \phi_2 f_{t-2}^A + \phi_3 f_{t-1}^{us} + \phi_4 f_{t-2}^{us} + \varepsilon_t^A$$

Note that the measurement equation and other transition equations of the baseline model introduced in Chapter 2 keep the same.

In this exercise, we fail to capture statistically significant coefficients of the US factor on Asian markets. The coefficients  $\phi_3, \phi_4$  nearly equal zero. Since we have proved that the U.S. is holding a dominant position on the global stock markets, most of the fluctuations originated in the U.S. have resulted in a worldwide co-movement and then influenced Asian stock markets. In other words, when the U.S. impacts Asian stock markets, it also influences other regions at the same time. Hence, such spread-out among all countries is captured by the world factor. In this empirical study, an additional spillover from the U.S. to Asian stock markets besides worldwide transmission through the world factor doesn't exist.

### 3.2.3 Spillovers between Asian and Latin American stock markets

Since we fail to capture an additional and direct spillover from the U.S. to Asian stock markets, another question that comes to mind is that it is possible to find a close linkage between two developing regions. To address the problem, we modify the baseline model to satisfy such assumption:

$$\begin{aligned} f_t^A &= \phi_{A1}f_{t-1}^A + \phi_{A2}f_{t-2}^A + \phi_{A3}f_{t-1}^{LA} + \phi_{A4}f_{t-2}^{LA} + \varepsilon_t^A \\ f_t^{LA} &= \phi_{L1}f_{t-1}^{LA} + \phi_{L2}f_{t-2}^{LA} + \phi_{L3}f_{t-1}^A + \phi_{L4}f_{t-2}^A + \varepsilon_t^{LA} \end{aligned}$$

Note that all other parts of the baseline model remain unchanged.

We are still not able to obtain significant coefficients of the LA factor in the Asian regional factor's law of motion, and coefficients of the Asian factor in the transition equation of the Latin American regional factor.

The investigation on spillover effects between different groups of countries remains lack of evidence for conclusions in this study. As explained in last section, such spillovers could be mostly captured by the world factor. Another possible reason is that since our research is only focused on relatively long term stock return volatility dynamics, the short term fluctuation and underlying spillovers between different stock markets are very likely to be canceled out and can't be captured on a monthly basis.

However, our study still provides valuable information for long term international investors that even with clear stock return volatility co-movements over the world and within regions, empirical evidence on spillovers on a monthly basis between two specific regions has not been found.

### 3.3 Financial globalization effects on world stock markets

Financial globalization is widely recognized to take place since middle 1980's. In order to address the issue on impacts of financial globalization on world stock markets, we need to extend the stock indexes price data back to 1970's. Due to lack of data from the Datastream for all 14 countries at the extended time range, we break the sample of 14 countries down to 9 countries. The new classification of countries is adjusted as follows:

Table 2: Classification of 9 countries

<b>World</b>	<b>Region</b>	<b>Country</b>
Common	North America	
		US
		Canada
	Europe	
		UK
		Germany
		Austria
		Belgium
	Asia	
		Hong Kong
		South Korea
		Taiwan

*Note:* The new classification has a limited number of countries due to lack of data.

We estimate the baseline model for two time periods: 1976-85 and 1986-2009. Table 3 gives the variance decomposition results for each country during the different time periods.

Table 3: Variance decomposition for 9 countries

	1976-1985 Share contributed by the <b>word</b> <b>factor</b>	1976-1985 Share contributed by the <b>region</b> <b>factor</b>	1986-2009 Share contributed by the <b>word</b> <b>factor</b>	1986-2009 Share contributed by the <b>region</b> <b>factor</b>
US	64.54%	0.27%	25.46%	5.96%
Canada	69.36%	6.02%	32.89%	8.27%
UK	6.70%	1.51%	75.29%	3.77%
Germany	10.55%	46.36%	42.15%	24.83%

Austria	1.95%	76.76%	5.88%	2.81%
Belgium	8.69%	13.68%	42.61%	15.55%
Hong Kong	38.84%	4.43%	23.72%	18.25%
South Korea	5.72%	0.92%	6.91%	36.27%
Taiwan	1.43%	1.16%	4.59%	34.78%

*Notes:* All results are estimated from variance decomposition as discussed in Chapter 2. The second column of the table shows shares of volatility fluctuation contributed by the world factor for each market before the financial globalization. The third column shows the shares contributed by the regional factor before 1985. The fourth and fifth columns represent results for after the financial globalization.

In North America, on average, around 65% of variation of stock volatility used to be explained by the world factor before financial globalization. The reason that caused this situation could be that the U.S. and Canada acted as a driving force of fluctuation in world stock markets prior to 1985. After financial integration took place, the world factor has become much less important in accounting for stock variation in North American markets. In other words, dominance of the U.S. in world stock markets has been getting weaker as financial integration becomes stronger. The regional factor is showed to be a small contribution for stock variation in North American markets, before and after financial globalization. Such insignificant regional co-movement in North American stock markets is always the case, no matter in the baseline model from the section 2.3.2 or the model in this section.

In Europe, the regional factor is always a substantial factor to explain the variation of stock return volatility. But the regional factor was able to account for a larger proportion of variation before the financial globalization than after, except for UK. Since financial globalization took effect, European stock markets have become a more important force to influence the world stock markets. The world factor is capable of explaining 42% of variation of stock volatility in Germany and Belgium and 75% in UK. The importance of the world factor for European stock markets even exceeded that for North America after financial integration. However, the regional

factor still accounted for a big fraction of volatility variation in Europe even though the fraction is getting smaller. With the standardized equity pricing system and similar domestic laws on equity investments within European stock markets, the regional co-movement should have been enhanced. The reason that caused the decrease in importance of the regional factor in Europe could be that partial regional co-movement within European stock markets is captured by the world factor when the European economy became a big effect on international markets.

For Asian stock markets, the regional factor was able to account for much bigger proportion of stock variation after 1986 than before. Since a financial crash occurred in 1987, Asian stock markets have been following more common monetary policies, and the intra-regional trade and investment in recent years are growing fast. The world factor has appeared to be losing importance in Asian markets, especially in Hong Kong, since financial globalization took place. In pre-1985, 39% of stock variation in the Hong Kong stock market was explained by the world factor, but it dropped to 24% after 1986. It demonstrates that Asian stock markets have become more independent and relied less on those developed stock markets over time, resulting from highly growing economies and more mature financial systems.

### **3.4 Conclusions**

In this Chapter, we investigate the dominant position of the U.S. on the global stock markets and spillover effects between countries or regions by modifying the baseline model. Empirical results show that in last two decades, U.S. stock market was still playing a major role in determining the worldwide co-movement of stock return volatility. But little evidence of significant spillovers between regions has been found. In reality, two specific stock markets could be highly correlated in the short run. But this study is focused on relatively long-term

analysis based on monthly stock return volatility. The short term correlation between stock markets could be canceled out on a monthly basis. The conclusion from our study is that the existence of significant long term relationship between two stock markets has not been proved by data.

Furthermore, we analyze effects of financial integration on world stock markets by extending the time horizon to 1967-2009 and cutting down the country sample to 9 countries due to lack of data for some countries in the new time range. The results show that the dominance of the U.S. stock market in world stock markets has been getting weaker since international financial markets became more integrated. Emerging stock markets have become more independent of developed and mature markets after financial globalization. The regional factor started playing an important role in Asian stock markets, which is in large part because of the fast growing economy and more mature financial system.

For the future research, extending time horizon and adjusting sample countries to investigate spillovers across world stock markets would be a good direction to continue this work. Another interesting extension is to decompose stock return and volatility together into several orthogonal factors, in which way the relation between stock return and volatility can be investigated. We can address the problem that how much variation of stock returns is determined by volatility common factors, which can be interpreted as the price of risk.

## Appendix:

The baseline model can be rewritten in state space model pattern:

$$y_{it} = a_i + [\lambda_{i1} \ 0 \ \lambda_{i2} \ 0 \ 1 \ 0] \begin{bmatrix} f_t^w \\ f_{t-1}^w \\ f_t^r \\ f_{t-1}^r \\ u_{it} \\ u_{i,t-1} \end{bmatrix}$$

Subject to:

$$\begin{bmatrix} f_t^w \\ f_{t-1}^w \\ f_t^r \\ f_{t-1}^r \\ u_{it} \\ u_{i,t-1} \end{bmatrix} = \begin{bmatrix} \phi_1^w & \phi_2^w & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \phi_1^r & \phi_2^r & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \varphi_{i1} & \varphi_{i2} \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} f_{t-1}^w \\ f_{t-2}^w \\ f_{t-2}^r \\ f_{t-2}^r \\ u_{i,t-1} \\ u_{i,t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^w \\ 0 \\ \varepsilon_t^r \\ 0 \\ e_{it} \\ 0 \end{bmatrix}$$

Gibbs-sampling for estimating parameters is showed in this section as follows:

For generating  $\Psi$  for each country  $i$ , we know that

$$y_t = A + \Lambda \ f_t + u_t$$

$$u_{it} = \psi_{i1} u_{i,t-1} + \psi_{i2} u_{i,t-2} + e_{it}$$

So, in matrix notation, we can get

$$\tilde{u}_{iT} = U_i \tilde{\psi}_i + \tilde{e}_{iT}, \quad \tilde{e}_{iT} \sim N(0, \sigma_i^2 I_T)$$

Prior distribution is assumed to be  $\tilde{\psi}_i \sim N(a_i, b_i)$ .

Posterior distribution can be calculated as

$$\tilde{\psi}_i \mid \Lambda_i, \sigma_i^2, f_i, y_i \sim N(a_i^*, b_i^*)$$

where

$$a_i^* = (b_i^{-1} + \sigma_i^{-2} U_i' U_i)^{-1} (b_i^{-1} a_i + \sigma_i^{-2} U_i' \tilde{u}_{iT})$$

$$b_i^* = (b_i^{-1} + \sigma_i^{-2} U_i' U_i)^{-1}$$

For generating  $\Phi$ , we have

$$f_t = \Phi_1 f_{t-1} + \Phi_2 f_{t-2} + \varepsilon_t$$

Prior distribution:  $\tilde{\phi}_i \sim N(c_i, d_i)$

Posterior distribution:

$$\tilde{\phi}_i | f_i, y_i \sim N(c_i^*, d_i^*) \quad i=1, 2, 3$$

where

$$c_i^* = (d_i^{-1} + F_i' F_i)^{-1} (d_i^{-1} c_i + F_i' f_{iT})$$

$$d_i^* = (d_i^{-1} + F_i' F_i)^{-1}$$

For generating  $\sigma_i^2$ , we know from above

$$\tilde{u}_{iT} = U_i \tilde{\psi}_i + \tilde{e}_{iT}, \quad \tilde{e}_{iT} \sim N(0, \sigma_i^2 I_T)$$

Prior distribution is  $1/\sigma_i^2 \sim \Gamma(\frac{v_i}{2}, \frac{w_i}{2})$

Posterior distribution is

$$1/\sigma_i^2 | \tilde{\psi}_i, \Lambda_i, f_i, y_i \sim \Gamma\left(\frac{v_i + (T-2)}{2}, \frac{w_i + (\tilde{u}_{iT} - U_i \tilde{\psi}_i)'(\tilde{u}_{iT} - U_i \tilde{\psi}_i)}{2}\right)$$

For generating  $\Lambda$ , we need to do some adjustment. Substitute  $y_t = A + \Lambda f_t + u_t$

into  $u_t = \Psi_1 u_{t-1} + \Psi_2 u_{t-2} + e_t$ . Take  $i=1$  for example,

$$y_{1t} = \lambda_{11} f_t^w + \lambda_{12} f_t^d + u_{1t}$$

$$u_{1t} = \psi_{11} u_{1,t-1} + \psi_{12} u_{1,t-2} + e_{1t}$$

Then, we can get



$$y_{1t} - \lambda_{11}f_t^w + \lambda_{12}f_t^d = \psi_{11}(y_{1t-1} - \lambda_{11}f_{t-1}^w + \lambda_{12}f_{t-1}^d) + \psi_{12}(y_{1t-2} - \lambda_{11}f_{t-2}^w + \lambda_{12}f_{t-2}^d) + e_{1t}$$

$$y_{1t} - \psi_{11}y_{1t-1} - \psi_{12}y_{1t-2} = \lambda_{11}(f_t^w - \psi_{11}f_{t-1}^w - \psi_{12}f_{t-2}^w) + \lambda_{12}(f_t^d - \psi_{11}f_{t-1}^d - \psi_{12}f_{t-2}^d) + e_{1t}$$

$$y_{1t}^* = \lambda_{11}f_{1t}^{w*} + \lambda_{12}f_{1t}^{d*} + e_{1t}$$

By using the same method of generating  $\Phi$ , we can get the sampling for  $\Lambda$ .

For estimating unobserved factors, we rewrote the model into a state space pattern and Kalman Filter is applied to achieve the estimate of factors.

It's important to monitor the convergence of the computation. We did so in a number of ways. First, we restart the computation from a number of different initial values, and the procedure always converges to the same results. Second, we discard the first 5,000 drawings and take the next 15,000 drawings. We try more drawings and the results show the same.

## References

- Bae, Jinho and Kim, Chang-Jin and Nelson, Charles R., (2007) “Why are stock returns and volatility negatively correlated?”, *Journal of Empirical Finance* 14, 41- 58.
- Bakshi, Gurdip and Madan, Dilip (2006), “A Theory of Volatility Spreads”, *Management Science* Vol 52, No. 12, pp. 1945-1956
- Bali, Turan G. and Hovakimian, Armen (2009), “Volatility Spreads and Expected Stock Returns”, *Management Science* Vol 55, No.11 pp. 1797-1812
- Bekaert, Geert and Harvey, Campbell R. (1995) “Time-varying world market integration,” *Journal of Finance* 50, 403-444
- Bekaert, Geert and Harvey, Campbell R. (1997) “Emerging equity market volatility” *Journal of Financial Economics* 43 (1997) 29-77
- Bekaert, Geert and Harvey, Campbell R. (2000) “Foreign speculators and emerging equity markets,” *Journal of Finance* 55, 563-613
- Bekaert, G. and Wu, G. (2000) "Asymmetric Volatility and Risk in Equity Markets," *Review of Financial Studies* 13, 1-42.
- Bekaert, Geert and Harvey, Campbell R. and Ng, Angela (2005) “Market integration and contagion,” *Journal of Business* 78, 39-70
- Bekaert, Geert and Hodrick, Robert J. and Zhang, Xiaoyan (2009) “International stock return comovements” *The Journal of Finance* Vol. LXIV, No.6
- Black, Fischer and Scholes, Myron (1973) “The Pricing of Options and Corporate Liabilities”, *Journal of Political Economy* 81 (3): 637–654.
- Brooks, Robin, and Del Negro, Macro (2002) “International diversification strategies,” Working paper, Federal Reserve Bank of Atlanta

- Brooks, Robin, and Del Negro, Marco (2004) "The rise in comovement across national stock markets: market integration or IT bubble?," *Journal of Empirical Finance* 11, 649-680
- Brooks, Robin, and Del Negro, Marco (2005) "Country versus region effects in international stock returns," *Journal of Portfolio Management* 31, 67-72
- Campbell, J. Y., and Hentschel, L. (1992) "No News is Good News: An Asymmetric Model of CHANGING Volatility in Stock Returns" *Journal of Financial Economics* 31, 281-318.
- Del Negro, Marco and Otrok, Christopher, (2008) "Dynamic factor models with time-varying parameters: measuring changes in international business cycles," *Staff Reports* 326, Federal Reserve Bank of New York
- Diebold, Francis X. and Yilmaz, Kamil (2009) "Measuring financial asset return and volatility spillovers, with application to global equity markets" *The Economic Journal* 119 (January), 158-171
- Glosten, L.R. and Jagannathan, R. and Runkle, D.E.(1993) "On the relation between the expected value and the volatility of the nominal excess return on stocks," *Journal of Finance*, 48, 1779-1802
- Karolyi, G.A. (1995) "A multivariate GARCH model of international transmissions of stock returns and volatility: the case of the United States and Canada," *Journal of Business and Economics Statistics* 13, 11-25
- Karolyi, G.A. and Stulz, R. M (1996) "Why do markets move together? An investigation of US-Japan stock return comovement using ADRs," *Journal of Finance* 51, 951-986
- King, M. A., and Wadhwani, S.B. (1990) "Transmission of volatility between stock markets," *Review of Financial Studies*, 3, 5-33

- King, Mervyn, Sentana, Enrique, and Wadhwani, Sushi (1994) "Volatility and links between national stock markets", *Econometrica*, Vol.62, No.4
- Kose, M.A., Otrok, Christopher, and Whiteman, C.H. (2003) "International Business Cycles: World, Region, and Country-Specific Factors" *American Economic Review*, 93, 1216-1239
- Ng, Angela (2000) "Volatility spillover effects from Japan and the US to the Pacific-Basin" *Journal of International Money and Finance* 19 (2000) 207-233
- Ng, V. M., Engle, R. F. and Rothschild, M. (1992) "A multi-dynamic factor model for excess returns," *Journal of Econometrics*, 52, 245-266
- Omori, Yasuhiro, Chib, Siddhartha, Shephard, Neil, and Nakajima, Jouchi (2007) "Stochastic Volatility with Leverage: Fast and Efficient Likelihood inference" *Journal of Econometrics* 140, 425-449
- Otrok, Christopher and Whiteman, Charles H. (1998) "Bayesian leading indicators: measuring and predicting economic conditions in Iowa" *International Economics Review* Vol. 39, No. 4
- Wu, G. (2001) "The Determinants of Asymmetric Volatility," *Review of Financial Studies* 14, 837-859